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Fusion of visible and infrared images using global entropy and gradient constrained regularization

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HIGHLIGHTS

- The image fusion problem is transformed into image optimization problem.
- Global maximum entropy is used as the main factor in cost function.
- The gradient constraint is designed into as the regularized term.
- The weight value matrix is used based on the minimization of the cost function.

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ABSTRACT

Infrared and visible image fusion has been an important and popular topic in imaging science. Dual-band image fusion aims to extract both target regions in infrared image and abundant detail information in visible image into fused result, preserving even enhancing the information that inherits from source images. In our study, we propose an optimization-based fusion method by combining global entropy and gradient constrained regularization. We design a cost function by taking the advantages of global maximum entropy as the first term, together with gradient constraint as the regularized term. In this cost function, global maximum entropy could make the fused result inherit as more information as possible from sources. And using gradient constraint, the fused result would have clear details and edges with noise suppression. The fusion is achieved based on the minimization of the cost function by adding weight value matrix. Experimental results indicate that the proposed method performs well and has obvious superiorities over other typical algorithms in both subjective visual performance and objective criteria.

1. Introduction

Image fusion technology has been widely applied in many fields, such as military affairs [1], remote sensing [2], and medical science [3]. Image fusion is used to combine multiple registered images of the same scene from multiple sensors into a single one. The goal of fusion is to generate fused image with important information from multiple sources, so dose fusion of visible (VI) and infrared (IR) images. The VI image usually contains abundant object details. And IR image which is captured with particular target information also should be considered for information extraction. Therefore, the fusion of VI and IR images is expected to maintain both advantages of IR and VI images [4,5]. More information could be obtained to well understand the scene.

Recently, plenty of fusion approaches have been proposed, especially for pixel-level-based VI and IR image fusion. The most common method is average fusion, which is to average of two source images pixel by pixel. Usually, this rule would make a blurred result with low contrast [6]. Since the image features are sensitive to human visual system (HVS), there exist many methods based on multi-resolution or multi-scale, including wavelet and curvelet transform based approaches[7–9], contrast pyramid [10], contourlet transform, ratio pyramid [11], and morphological pyramid [12], etc. Those methods usually include three steps: (1) the images are decomposed into different scales; (2) the coefficients are fused using proper rules; (3) the fused results are reconstructed by images in different scales. These kinds of approaches can perform well, but they would smooth some image details or create

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artifacts because of the multi-scale decomposition [6,13]. Ma and his partners developed an IR and VI image fusion method via gradient transfer and total variation minimization [14], which performs well, sharpening infrared images with more appearance details. Features analysis is important in image fusion, thus principal component analysis (PCA) and independent component analysis (ICA) are introduced as the fusion rules [15,16]. Because of the loss of some information in PCA and ICA analysis, details and other information loss make it not suitable for IR and VI image fusion. Li et al. [13] mentioned a weighted average fusion method based on guided filter. The main drawback is the poor efficient performance, and the saliency maps generated may not well represent the visual attention. Morphology theory is also utilized to extract image regions for image fusion. Then a method based on multi scale center-surround top-hat transform for IR and VI image fusion is proposed [4]. Thanks to the good image regions extraction, the fusion performs wonderfully. However, the three selectable parameters have a wide range of values, which make the algorithm difficult for inexperienced users. And the computational speed is another problem, and there is possibility to accelerate. The visual saliency detection is popular recently [17–20], and this theory could be well applied in image fusion. Creating saliency features map based on local Gaussian difference, researchers have applied saliency preserving idea in image fusion [21]. The authors of this paper also have made great effort in saliency detection-based image fusion [22–24]. These methods perform very well with details enhancement, especially for IR and VI images. But these methods run slowly sometimes.

Furthermore, entropy value is widely used for evaluating fused images. The more information the fused image inherits from original sources, the larger value the result has. As a result, the larger entropy value indicates that fused result obtains better quality. In some researches, people have introduced entropy into image fusion algorithms [25,26], using the entropy as a tool to derive parameters.

In our study, we try to transform the image fusion problem into image optimization problem, by taking the advantages of global maximum entropy, together with gradient constraint as the regularized term. Then, the cost function is designed. Global maximum entropy could make the fused result inherit as more information as possible from sources. Using gradient constraint, the fused result would have clear details and edges with noise suppression. The fusion is achieved with weight value matrixes, which are optimized based on the minimization of the cost function. According to experimental results, the fusion has a good performance, with good visual quality and details preserving. Besides, objective image fusion quality metric methods also indicate the advantages of proposed approach. Meanwhile, the algorithm runs fast.

The main contributions of the proposed scheme can be summarized as follows:

1. The image fusion problem is transformed into image optimization problem. This transformation would help understanding image fusion from another novel perspective, which is different from previous entropy-based method.
2. Global maximum entropy is used as the main factor in cost function. This process would improve the quality of the fused image, by inheriting as more information as possible from source images.
3. The gradient constraint is designed and applied as a regularized term, which could suppress noise effectively. Meanwhile, the details would be enhanced.
4. The fusion process is implemented with weight value matrixes, which are optimized based on the minimization of the cost function. The weight value matrixes could enhance the edges and details in fused result.

In this paper, the fusion algorithm is structured as follows. The theory is introduced in Section 2. In Section 3, the details of proposed method are presented, including the derivation of optimization. The experimental results and discussion are done in Section 4. And then the conclusions are drawn.

2. Mathematical theory

2.1. Frieden Entropy-based fusion theory

Entropy is a good objective metric for image fusion. The more information inherits from original sources, the larger value the result has. With the source images A (IR image) and B (VI image), we are eager to obtain the fused result *F*, which satisfies the maximum entropy rule:

$$F = \arg\max_{F} H(F) \tag{1}$$

where $H(F)$ is defined using Frieden Entropy for each pixel (i,j) [27]:

$$H(F) = -\sum_{i,j} F_{ij} \ln F_{ij} \tag{2}$$

And in our design, we adopt weighted fusion rules. For arbitrary pixel, the fused result F_{ij} is determined by weighted sum of IR image A and VI image B as follows:

$$F_{ij} = X_{ij}A_{ij} + Y_{ij}B_{ij} \tag{3}$$

In Eq. (3), X and Y are the weight matrixes we need. Then, this problem is transformed into an energy minimization problem as shown in Eq. (4):

$$F = \arg\min_{F} E_1 = -H(F) s.t. F_{ij} = X_{ij}A_{ij} + Y_{ij}B_{ij} \tag{4}$$

It is usually assumed that the derivatives of a sharp image follow a Gaussian distribution with zero mean. If one expects a fused image with less noise and smooth, this prior could be used to constrain fusion process. And, the derivative is calculated using some filters h_i ($i = 1,2\ldots$). With our analysis, the edge region in fused result seems more important. We are eager to make the edge area follow this rule, thus we introduce a weight matrix *M* to solve this problem. The edge region would relatively have larger weight.

Like Eq. (4), the energy function is expressed as E_2, with adding *M*, E_2 finally is defined as:

$$E_2(F) = (\|h_1 * F\|_2^2 + \|h_2 * F\|_2^2)M. \tag{5}$$

where $\| \quad \|_2$ denotes the second order norm operator, h_i are selected as first order of the horizontal and vertical derivative filters: $h_1 = [-1\,1]$, $h_2 = [-1\,1]^T$. And Eq. (5) can be rewritten as

$$E_2(F) = \sum_{i,j} [(F_{ij+1} - F_{ij})M_{ij}]^2 + [(F_{i+1j} - F_{ij})M_{ij}]^2 \tag{6}$$

Finally, this fusion problem is transformed into an energy minimization problem as follows:

$$F = \arg\min_{F} (E = E_1 + \lambda E_2) s.t. F_{ij} = X_{ij}A_{ij} + Y_{ij}B_{ij} \tag{7}$$

where $E = \sum_{ij}\{F_{ij}\ln F_{ij} + \lambda([(F_{ij+1} - F_{ij})M_{ij}]^2 + [(F_{i+1j} - F_{ij})M_{ij}]^2)\}$ and where the scalar λ is a regularized factor, which is set to balance the two terms.

2.2. The weight matrix M

In fused images, the edge area should be clear with high contrast. We introduce the prior in Section 2.1 to pursuit a fused image with less noise and smooth but high contrast, imposing weight matrix *M* on fusion. Weight matrix is designed for local weight of fusion. This matrix could help locally control smooth and detail